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The influence of climate change on an endangered riparian plant species: The root of riparian Homonoia

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ABSTRACT

The root of riparian Homonoia (RRH), a medical plant with high economic value, is mainly distributed at riparian area in Southeast Asia. Its population has declined significantly, and the species has become endangered in recent decades. Understanding the habitat requirement, evaluating the habitat quality, and predicting its potential habitat are significant for protecting this species. Here, 223 occurrence records of the RRH were collected globally. The key eco-factors influencing species distribution were selected based on correlation analysis and principal component analysis. Habitat suitability simulation found on four climate-warming scenarios (RCP 2.6, RCP4.5, RCP6.0 and RCP8.5), given by IPCC. The results found that both the suitable area and the suitability of the RRH habitat increase as the climate warming. The increasing range achieved a maximum at RCP4.5.

1. Introduction

Habitat degradation, fragmentation, loss and habitat migration change the space of biology's living patterns, resulting in less favorable and suitable habitats for the species (Nogué et al., 2009). This cycle is the main reason for species being endangered, extinction and decline in biodiversity (Bogich et al., 2012; Heinrichs et al., 2016). It was found that approximately one-fifth of all plant species are in danger due to the change of habitat as of 2010 (Brummitt and Bachman, 2010). Habitat change has various causes, among these, climate change and human activities (e.g., land use, dam construction) are the most important, and cause the habitat quality to degrade and habitat lost (Grimm et al., 2008; Burbano, 2013). Climate change has a profound impact on species' distribution range (Hamann and Wang, 2006; Barrett et al., 2013), and endangered many plant species. It results in species change, extinction, turnover and changes in the communities' structure and population. Since the climate is very important to vegetation, the Intergovernmental Panel on Climate Change (IPCC) using different models to simulate climate change and had come into possession of different scenarios. Based on this many researchers use to simulate the change of vegetation habitat, in order to investigate the requirements of species, plan conservation reserves and understand patterns of biodiversity (Pettorelli et al., 2012). Under such circumstances, the climate-matching approach has positives and negatives aspect of impacts. Some researchers, use model to give substantial evidence for climate warming that will bring positive ecological effects, or make vegetation belt move along with the climate change. Vieilledent et al. (2013) estimated the vulnerability of three endangered baobab species with climate change tending to extend the suitable habitat of the species. Others found that climate change will be infaust to the growth and development of plants. Thomas et al. (2004) found that 15–37% of species in theirs ample of regions and taxa would be committed to extinction on the basis of mid-range climate-warming scenarios for 2050. Hällfors et al. (2016) found that the suitable climate for the species tended to shift toward the north and east as the climate change. There are also many other research studying on how climate change influences species distribution (Aguayo et al., 2014; Rohr et al., 2011).

The Root of Riparian Homonoia (RRH, *Homonoia riparia Lour*) (Fig. 1) is a medical plant. It has important medical and ecological value, however, the habitat of RRH has been found decreasing sharply in Yunnan Province, China (Yi et al., 2016). Therefore, it is very important to evaluate the habitat of RRH and need swift action to protect this species. Species distribution models (SDMS) has a distinct meaning of simulating species habitat suitability (HS) at different spatial scales (Araujo et al., 2005). It was developed to predict the potential distribution between species records and environmental

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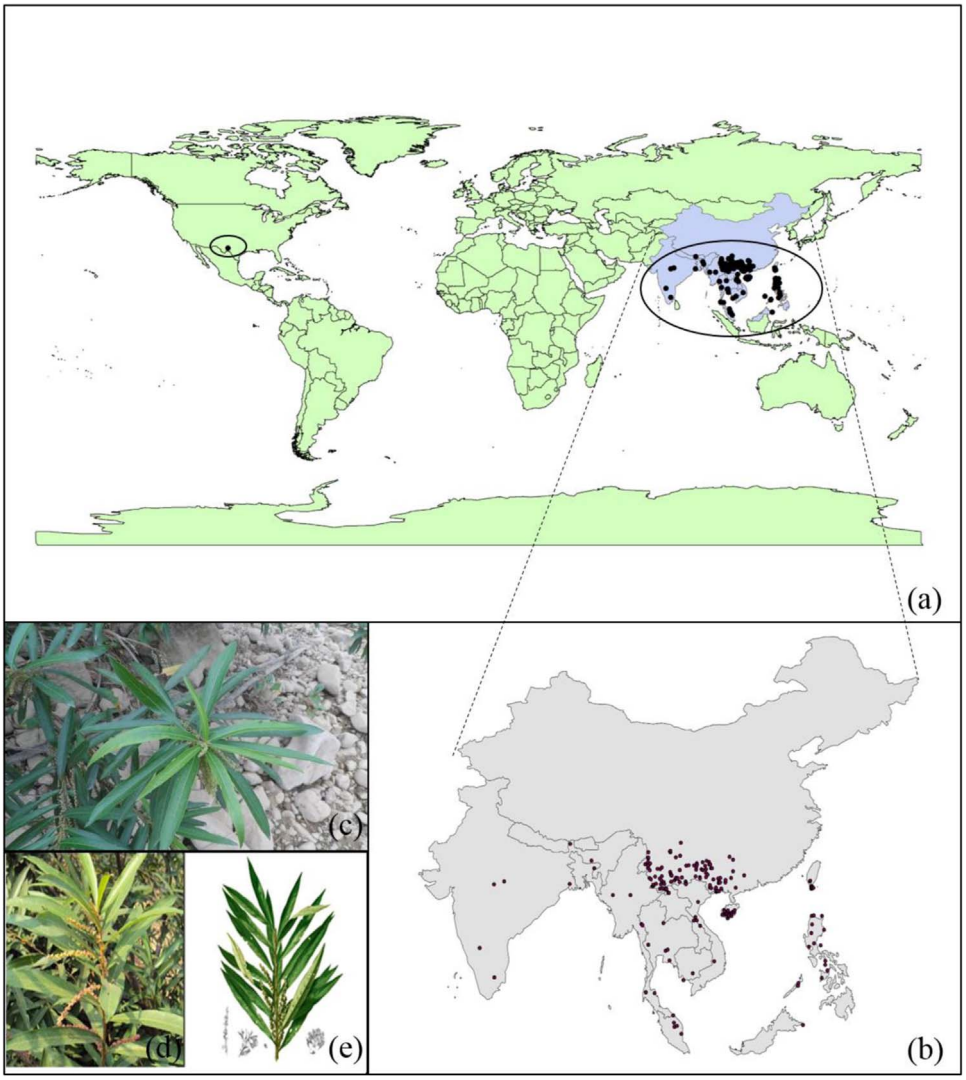

Fig. 1. (a) Map of world and the distribution countries; (b) distribution of the main rivers and the RRH's presence points in mainly countries (including Vietnam, Laos, Cambodia, Thailand, Burma, Brunei, Malaysia, Singapore, Indonesia, Philippines, and East Timor); (c, d) photos of RRH in the field; (e) pictorial handbook of RRH (including flower and seed).

characteristics of those sites (Raxworthy et al., 2003; Franklin, 2010). SDMS have been committed applying to the researchers conducted on ecology, conservation biology and environmental sciences. Several models such as Maxent, GARP, DOMAIN, BIOCLIM, CART, GAM, and GLM are widely used in predicting species distribution. Models are used to show how the existing environmental conditions restrict the geographic distribution of species (Yi et al., 2007; Domisch et al., 2015) in predicting the niche onto a map and using probability to reflect the species preference habitat (Phillips et al., 2009). For using SDMS, the basic work need is to collect comprehensive data but there are some problems about obtaining the information due to the lack of data and the obstacle of statistical work, result in the absence of species information and makes SDMS inapplicable. In consequence more attention has been given to their potential use to inform species conservation planning when the species distribution data are incomplete (Rodrigues, 2011; Lawler et al., 2010). Among these models, Maximum entropy theory (Maxent, Maximum Entropy, MAXENT) has better results when there is incomplete data availability and it has been successfully applied in previous research on predicting the distribution of species. (Phillips et al., 2004; Estes et al., 2013; Elith et al., 2011). According to Wang et al. (2007), Maxent is one of the best models based on using AUC (area under the receiver operating characteristic curve) value to detect the quality of model, and it is the least biased estimate possible from the existing information, it provides a constructive criterion for establishing probability distributions based on partial knowledge with in a small sample data records, it can be more effective tool for biodiversity conservation planning, monitoring and management. The model is widely used to predict endangered species' distribution (Kumar and Stohlgren, 2009) and the potential distribution of invasive species (Monica et al., 2016; Gama et al., 2016). It has also been used to predict the distribution range of plant diseases and insects; to model the distribution of species, communities or ecosystems; to assess the impacts of climate, land use and other environmental changes on species' distributions (Thomas et al., 2004; Andriamasimanana and Cameron, 2013); to evaluate the risk of species' invasion and amplification (Beerling et al., 1995; Peterson 2004); to filter unsurveyed areas with high suitability for precious endangered species (Engler et al., 2004); to contribute to site selection of natural conservation areas (Ferrier, 2002); and to identify areas for species reserves and reintroduction (Adhikari et al., 2012). In this context, we explored the potential distribution of RRH in current situation and under different climate warming scenarios. First, we filter the eco-factors based on correlation analysis and principal component analysis. Second, the sample data information with eco-factors selected, to develop a model that tries to explore the distribution of RRH. Then, using GIS to draw output of the model, a map of probability of occurrence of RRH for the entire world territory was generated. Finally, Maxent is used to predict the redistribution of RRH under different

climate scenarios. This analysis would prove the impact of climate change to RRH, positive or negative, as a future indicator of habitat quality, allowing us to make objective to cultivate the appropriate environmental as required of the species.

2. Species and habitat

The Root of Riparian Homonoia (*Euphorbiaceae*) (Fig. 1) is an evergreen shrub that is 1 ~ 3 m high. The RRH is a medicinal plant and can be used to treat conditions such as hepatitis, joint pain, stomachache, and empyrosis (Chen, 1977). The root decoction of this plant is used as laxative and diuretic and also used in the treatment of piles, stone in the bladder, gonorrhea, syphilis and thirst (www.flowersofindia.net). Seeds contain fatty acid that most plant part contains tannin. The bark contains cyanogenic glycosides. It is a good source of fire wood because the woody roots, steams and branches are hard and high energy value (Hanum and Maesen, 1997). Its stem and leaves are used to depurate the skin of diseases. Its wood is used in an infusion against malaria. The tree not only acts as an important source of food but is also a shelter for a wide range of animals. The RRH is a deep-rooted tree, and it has good resistance to drowning and scouring, effectively prevents erosion, fixes sands and reinforces dikes (Wei, 1992).

It is mainly distributed in Southeast Asian countries (including Vietnam, Laos, Cambodia, Thailand, Burma, Brunei, Malaysia, Singapore, Indonesia, Philippines, and East Timor) and south of China (e.g., Yunnan Province, Guangxi Province, Guangdong Province, Taiwan Province; Institute of Botany, 1972; Kumar, 2011). It has other aliases: Shuima, Xiagongchashu, Shuizhuimu, Xiyangliu in China. The RRH grows in warm and humid areas, and it is an archaeophyte. Its main living environments are river banks, sand by rivers, rocky places beside streams and brushes on the hillside where the altitude is 50–1400 m (Kumar, 2011). Investigations in recent years have shown that the habitat of RRH has been found decreasing sharply in Yunnan Province, China (Yi et al., 2016) and the number of the RRH worldwide has decreased since the 1950s (Zhao et al., 2014).

3. Methods

3.1. Data sources

Of the 223 occurrence records of the RRH globally were obtained from databases including the Global Biodiversity Information Facility (http://www.gbif.org), the National Specimen Information Infrastructure (http://www.nsii.org.cn/), the Chinese Virtual Herbarium (http://www.cvh.org.cn/) and the literature (Wang et al., 2000). Climate factors are the environmental dimensions that are mainly examined to build a niche-based model predicting a species' distribution. 19 bioclimatic variables have been considered to be the most typical variable to establish the species distribution models to forecast the species' spreading conditions (Guisan et al., 2007; Molloy, 2014). The highest-resolution (30 arc-seconds (approximately 1 km)) of 19 bioclimatic variables were collected from WorldClim's dataset (shown in Table 1; http://www.worldclim.org).

In the fifth IPCC report, using the total radiative forcing (RF) in 2100 as an index, four representative concentration pathways (RCPs) were set. These pathways represented scenarios in which the total RF in 2100 had reached 2.6 W/m^2, 4.5 W/m^2, 6.0 W/m^2 and 8.5 W/m^2 more than the value in the year 1750 (the fifth IPCC report). Of the four RCPs, RCP2.6 is the scenario in which global warming is the lowest, and it did not exceed 2 °C in 2100 compared to the years 1850–1900. Here, all the four scenarios are selected applying the Maxent to simulate the RRH's habitat suitability distributions. The climate data are climate projections for the year 2050 (averaged from 2041 to 2060) from the global climate models (GCMs) for the four scenarios. The data were obtained from the world climate website (http://www.worldclim.org).

3.2. Variables selection

To establish a model that has better performance with fewer variables and that avoids the multicol-linearity issue, climate conditions for 223 species' occurrence records were extracted using Arcgis9.3. Then, cross-correlations (Pearson correlation coefficient, r) and principal component analysis (PCA) were conducted among the 19 environment variables extracted. Only variables that were weakly correlated ($r < 0.8$) among the variables were kept for further analysis. For instance, the variables bio1 and bio6 were correlated ($r = 0.941$), as were bio6 and bio7 ($r = -0.849$). Considering the PCA result, bio6 was dropped, and both bio1 and bio7 were reserved. According to the contributions made by the 19 bioclimatic variables to every extracted principal component and the correlation analysis among the 19 bioclimatic variables, eight bioclimate variables (bio1, bio2, bio4, bio7, bio12, bio14, bio15, bio19) were reserved (Table 1). In addition, other precipitation and extreme temperatures were chosen that had a poor relation with bioclimate variables, including Pre1, Pre7, Tmin7 and Tmax7. Topography factors (including altitude and slope) were also considered when building the model.

3.3. Maximum entropy (MaxEnt) model

Given a random variable ξ that has n potential results, X_1, X_2, …,X_n, for which the occurrence probabilities are p_1, p_2, …,p_n, respectively. The entropy of ξ is given by the formula Jaynes (1957):

$$H(\xi) = \sum_{i=1}^{n} p_i \log \frac{1}{p_i} = -\sum_{i=1}^{n} p_i \log p_i$$

The Maxent model uses the maximum entropy principle to predict a species' (including animals and plants, even some viruses) distribution in ecology. The idea of the model is to predict and analyze the distribution of a species in the specified area by using the existing species distribution information and the main environmental factors that affect the distribution of species. The flexibility of the model lies in the fact that it can model any type of regional distribution of organisms, and the output can be determined according to the characteristics of the input data.

The model needs to input the known information distribution of species and environmental features. The input point can be set randomly as training data or test data. Generally, 75% of the input data are selected randomly for use as training data, and the remaining data are used for testing. Maxent provides output data in raw, cumulative, and logistic formats. Raw values are the primary output for Maxent. The logistic format is currently recommended because this format provides estimates of the probability of occurrence as predicted by included environmental variables (Phillips et al., 2006; Phillips and Dudík, 2008). The habitat suitability curves of each variable are calculated, and the contributions of each variable to the habitat model of RRH are shown in the software's built–in jackknife test.

Receiver operating characteristic (ROC) analysis was used to evaluate how well the Maxent model compared to a random prediction (Elith et al., 2009). The area under the ROC curve (AUC) is considered a measure of model performance in terms of sensitivity versus specificity. The software package Maxent employs the AUC to evaluate model performance. The index can be seen in Table 2.

Based on maximum entropy theory, the Java–based software package Maxent, which can be used for habitat suitability simulation, was developed by Phillips et al. (2006). The Maxent (version 3.3.3) used in this study was obtained from http://www.cs.princeton.edu/~schapire/MaxEnt/ and can be downloaded freely for scientific research.

Table 1
Environmental variables used for modeling the habitat suitability distribution of RRH.

Data source	Category	Variables	Abbreviation	Units
Fundamental GIS	Positional	The distance to the nearest river	Distance	m
	Topographic	Slope	Slope	Degree
WorldClimate	Topographic	Altitude	Altitude	m
	Bioclimatic	Annual Mean Temperature	Bio1	℃
		Mean Diurnal Range (Mean of monthly (max temp–min temp))	Bio2	℃
		Temperature Seasonality (standard deviation *100)	Bio4	Dimensionless
		Temperature Annual Range	Bio7	℃
		Annual Precipitation	Bio12	mm
		Precipitation of Driest Month	Bio14	mm
		Precipitation Seasonality (Coefficient of Variation)	Bio15	Dimensionless
		Precipitation of Coldest Quarter	Bio19	mm
		Maximum temperature of July	Tmax7	℃
		Minimum temperature of July	Tmin7	℃
		Precipitation of July	Pre7	mm
		Precipitation of January	Pre1	mm

Table 2
Model performance categorization (Swets, 1988).

AUC value	Model performance
< 0.5	Fails to describe reality
0.5	Pure chance
0.5–0.6	Fail
0.6–0.7	Poor
0.7–0.8	Fair
0.8–0.9	Good
> 0.9	Excellent

4. Results

4.1. Model performance and variables' contribution

Using Maxent calculates the RRH global distribution, the results showed that all ten generated training/testing models (for all records modeled) had a high level of performance compared to a random model (where the AUC would be 0.5). Test AUC were lower but close to the training AUC (shown in Fig. 2). The training AUC values were 0.987, and the test AUC values ranged from 0.972 to 0.983(the model runs ten times) (Fig. 2). The AUC index was employed to evaluate model performance (Phillips et al., 2006; Vallecillo et al., 2016). The simulation results are consistent with previous research that used the AUC value to prove the good performance of the model prediction results with presence–only data (Wisz et al., 2008; Giovanelli et al., 2010).

The variables' contribution and the results of the jackknife test analysis are shown in Fig. 3. Distance, Pre7, Bio7 and Bio12 resulted in very high gains (> 1.0) when they were used independently, indicating that these four variables contained more useful information by themselves than other variables did. Pre7, Bio7, Bio15 and distance were the four most important predictors of the RRH's habitat suitability distribution. The contribution of environmental factors can be seen in Table 3. The main environmental factors affecting the RRH's suitable habitat level were precipitation in July (Pre7, 37.6%), minimum temperature in July (Tmin7, 11.4%), temperature annual range (Bio7, 9.2%), and the distance from a river (Distance, 8.7%). The cumulative contribution of these four factors was 66.9%. These results indicated that Pre7, Bio7 and distance were key factors among all 15 variables for the RRH's habitat distribution regionally. These factors were also crucial in the RRH's growing period.

4.2. Variables' response to suitability

Response curves show the types of environmental characteristics that a species prefers. The responses of all 15 variables to the RRH's suitability are shown in Fig. 4.

Precipitation in July (Pre7) was the most important factor influencing the distribution and growth of the RRH. The main growth period of the RRH is in July, so the precipitation in July (Pre7) had a significant influence on the RRH's growth. In areas where the presence of the RRH

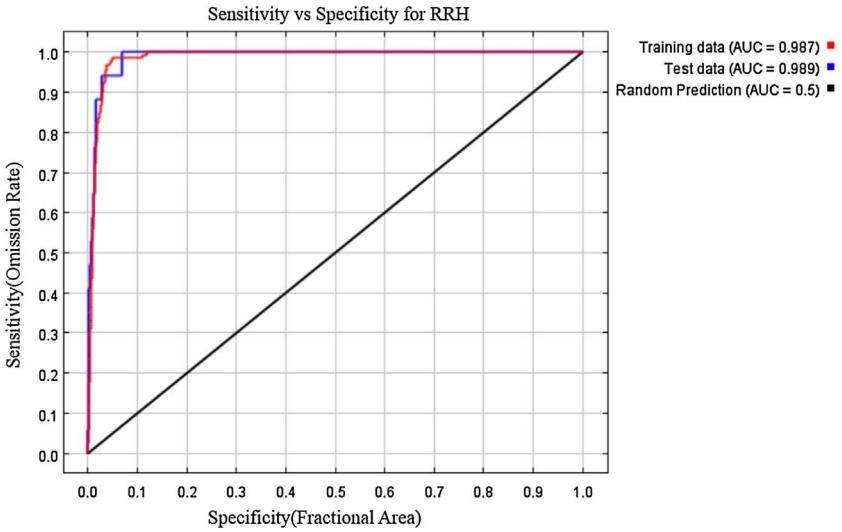

Fig. 2. ROC curves of training and test data of the RRH's habitat distribution globally in modeling.

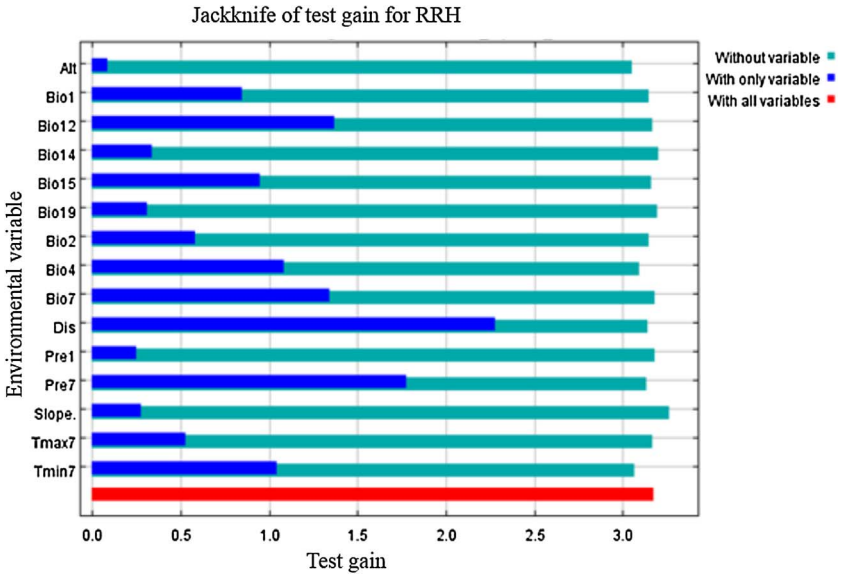

Fig. 3. Results of the jackknife test for the variables' contributions of the RRH's habitat distribution globally in modeling.

Table 3
Environmental variables and their percent contribution in Maxent model for RRH in the world.

Environmental variables	percent contribution
Precipitation of July(Pre7)	37.6
Minimum temperature of July(Tmin7)	11.4
Temperature Annual Range(Bio7)	9.2
The distance to the nearest river(Dis)	8.7
Slope	7.3
Precipitation of Driest Month(Bio14)	7.2
Precipitation Seasonality(Bio15)	6.3
Precipitation of Coldest Quarter(Bio19)	3.2
Annual Precipitation((Bio12))	3.1
Temperature Seasonality(Bio4)	2.7
Altitude(Alt)	2.7
Mean Diurnal Range(Bio2)	0.2
Annual Mean Temperature(Bio1)	0.2
Precipitation of January(Pre1)	0.2
Maximum temperature of July(Tmax7)	0

was higher than 0.6, Pre7 was higher than 500 mm, Bio7 was lower than 25 °C; Bio4 was lower than 4.3, indicating that the RRH grow in stable temperature, and Bio2 varied from 6.2 °C to 8.7 °C. Bio1 showed that the RRH preferred suitably warm climatic conditions, with temperatures between 20 °C and 27 °C. This finding could prove that RRH likes warm and humid areas (Van Steenis, 1978). When the suitability was higher than 0.4, Bio14 was higher than 12.5 mm, Bio15 was between 0 and 60, Bio19 was higher than 50 mm, and Bio12 was higher than 1100 mm. Precipitation is important in the RRH's growth period, but the influence of rainfall on the distribution of the RRH was not as important in the resting period. Temperature was another climate factor that influenced the distribution and growth of the RRH. According to the RRH's response to the temperature, Tmin7 had a high contribution to the distribution of the RRH, and 22–25 °C was a high suitability habitat. For topography, the distance to a river is a main factor (percent contribution is 8.7%) for determining the distribution of the RRH. The percent contributions of slope and altitude were 7.3% and 2.7%, respectively. Both have an unromantic influence on the RRH distribution.

4.3. Distribution of the RRH

By combining predicted results of the model with investigation, we can clearly see where the RRH primarily grows. The predicted habitat result is divided into four suitable levels: 0–0.2 is not appropriate, 0.2–0.4 is generally appropriate, 0.4–0.6 is moderately appropriate, and 0.6–1 is highly appropriate.

The main distribution of RRH was in the area of subtropical–tropical along riversides, which was a range of approximately 0° latitude to 29° northern latitude (Fig. 5). Highly appropriate areas were mainly distributed in the southwest of China and Vietnam, where with intensive rivers and abundant rainfall. Few areas in the southern part of North America were suitable for the growth of RRH. Africa has fewest suitable habitat area compared to other terrestrial area on same latitude, because it has minimal rainfall and cannot satisfy the RRH's growth. This result showed the potential suitable habitat area, which indicates the RRH's ideal habitat without human activities and other unknown factors influencing.

4.4. Climate change scenarios for RRH distribution on the global and regional scales

The habitat suitability of RRH was calculated under four climate change scenarios (RCP 2.6, RCP4.5, RCP6.0 and RCP8.5) (Figs. 6 and 7). Fig. 7 shows the main distribution area of RRH, which can be used to further analyze the change of RRH in different scenarios. In the world, the main distribution area of RRH mainly concentrated in the subtropical region. In different climate scenarios, habitat area of RRH has changed. According to the simulated results (Table 4), global warming would increase the potential habitat distribution of RRH. In the RCP4.5 scenario, the suitable area of the RRH extended more than the other scenarios. Especially for the highly appropriate category (0.6–1), the habitat suitability ranking was RCP4.5 > RCP6.0 > RCP8.5 > RCP2.6 > Present. This suggests that the habitat area of RRH will be largest in the RCP4.5 scenario, if the RCP value is greater or less than 4.5, the high suitable habitat area will be reduced. For the moderately appropriate category (0.4–0.6), RCP4.5 had the maximum area, and RCP2.6 had the lowest among the four scenarios. For the unsuitable category (0–0.2), RCP8.5 reached the maximum area. The Fig. 5 showed that high suitable for RRH grew reaching the most north area of 29°in current situation. As climate warming in different scenarios, distribution of RRH has changed, and high suitable area can move most north 30°N (Fig. 7).

5. Discussion

In this study we presented the change of habitat using a species-

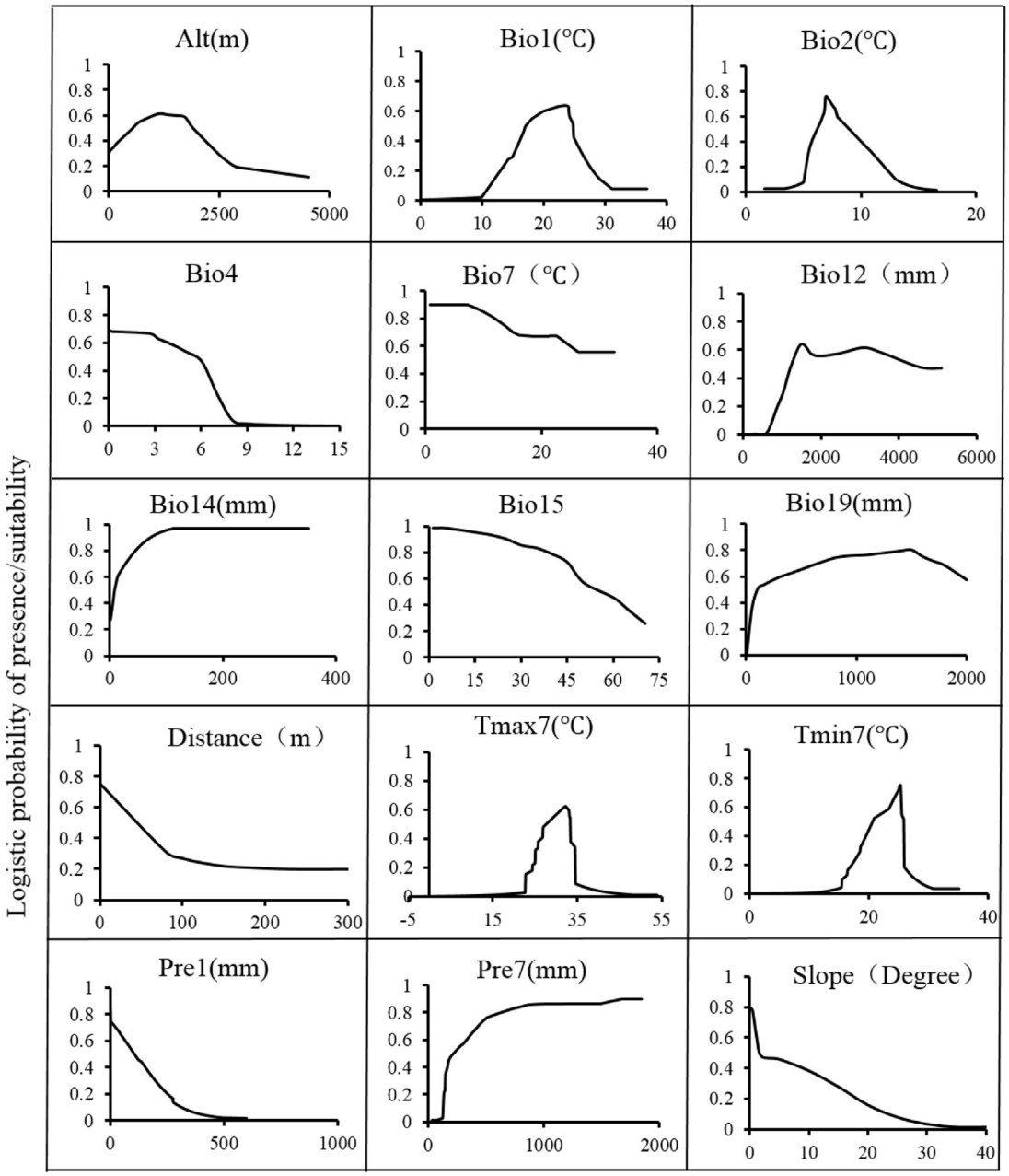

Fig. 4. Response curves of 15 environmental variables in modeling RRH's habitat distribution.

based approach (i.e. by means of Maxent). According to the simulation result, the suitable environment for RRH growth was found. The habitat suitability is diversely changed with different climate warming scenarios. Both the suitable area and the suitability of the RRH habitat increase with the climate warming. However, the quantity of RRH is decreased in recent years. Li et al. (2012) demonstrated that the RRH was severely impacted by inundation associated with dam construction.

5.1. Model performance and environmental variables response to species

The selected suite of environmental variables allowed the development of a robust model with an AUC of 0.972, the high overall model accuracy was the entirely interpretation of the environment variables and the existing data. Furthermore, the high explanation of response variance provides confidence in using the model to assess how landscape and climate features regulate the distribution of RRH. Compared with previous simulation, the AUC value was 0.84 in Yunnan (Yi et al., 2016) and 0.97 in worldwide. Previous researches indicated that the apparently high performance of the model may be influenced by their success at predicting the absences which predominate in the data for these species (Elith et al., 2006; Leathwick et al., 2008).

The relationship between environmental variables and species response was simulated by the model. Comparing with previous habitat simulation results of Yunnan province (China), the suitable range of variables such as altitude is different, suitable range between 50 and 2000 m in worldwide and 0–1600 m in Yunnan. However, other factors (including bio1, bio2, bio4, bio7, bio12, bio14, bio15, bio19, distance, slope) are similar.

In terms of variables contribution level, the contribution of climate conditions accounted for the vast majority to determine on the distribution of RRH (81.3%). Among the factors, the effect of rainfall on RRH occupied most of the proportion in climate conditions, which proves RRH is a hydrotactic plant and prefers to grow in humid and bountiful rainfall places (Van Steenis, 1978). Especially the factor of the precipitation of July (Pre7), July is the peak rainfall month in the subtropical zone. Lots of rain water can meet the exuberant growth of

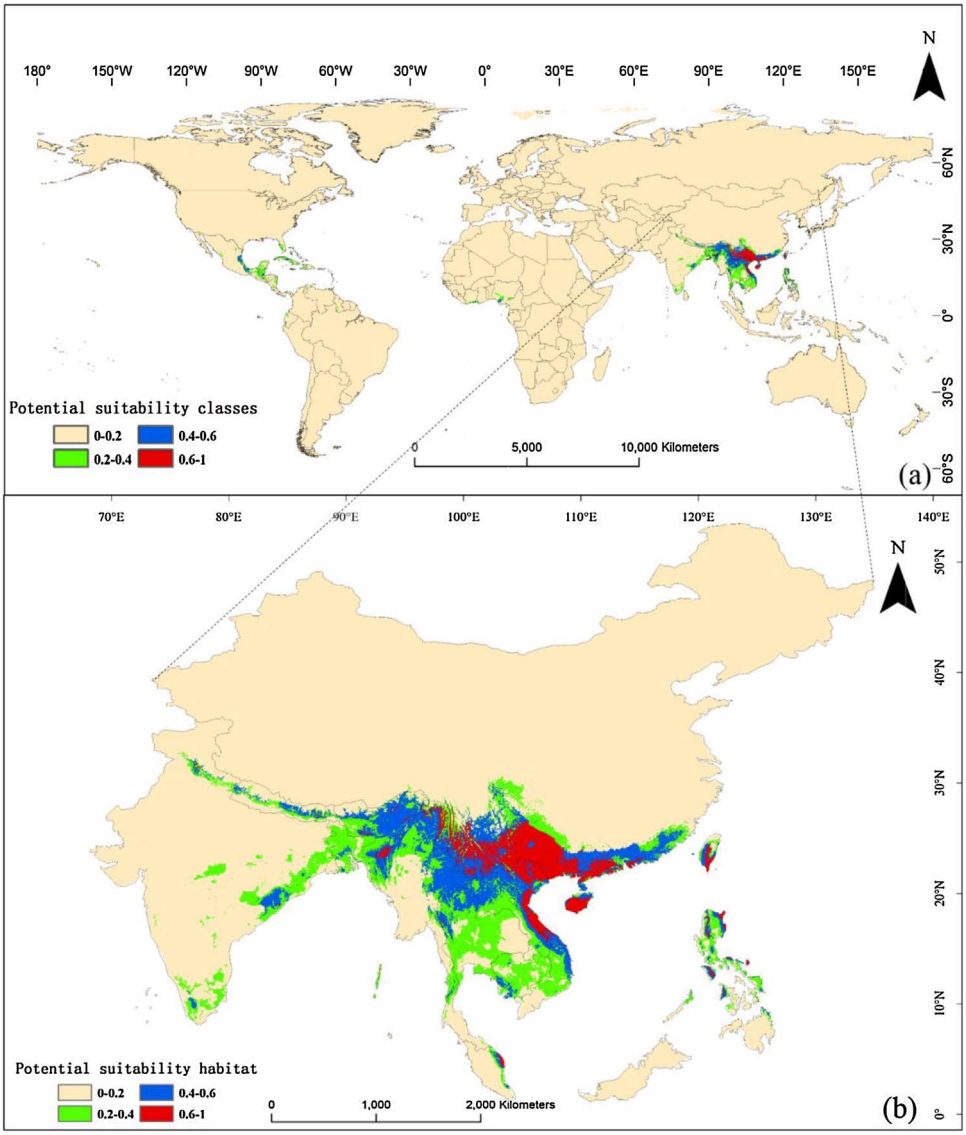

Fig. 5. The RRH potential habitat in global area (a) and mainly distribution countries (b).

RRH. Temperature also plays a very important role for the growth of RRH. If minimum temperature is lower than the temperature threshold of RRH in growth period, it would limit the growth and distribution of RRH. So the minimum temperature of July (Tmin7) provided considerable part information for predicting the potential distribution of RRH.

The distance from the river bank (Distance) in deciding distribution of RRH also possessed a certain contribution rate. The habitat of RRH is more suitable when it is closer to a river. This agrees well with the previous understanding of the RRH as a riparian plant (Tang, 1996). The RRH is a shrub on a hillside, but it may not be able to exist on high slopes. The curve showed that if the slope was higher than 40°, the RRH might not be able to live there. According to the response curves, when the altitude was higher than 2000m, the presence probability of the RRH was lower than 0.4. May be due to the high altitude area of temperature is not suitable for the growth of RRH. Generally, the appropriate altitude range (0m–2000m) was consistent with the descriptions of the RRH in Xishuangbanna Dai Medicine Zhi (XNDRO, 1980), which illustrated that the RRH mainly grew at altitudes ranging from 50 to 1400 m on riversides with sand (XNDRO, 1980).

To sum up, response curves well described the growing habitat of the RRH, such a response-effect framework for ecosystem resilience can be a useful tool for ecosystem management to define goals focusing on adaptation in changing environments (Sterk et al., 2013). And some researchers used Maxent to determine the environment where the species would like to live (Aida et al., 2010; Ying et al., 2016 Ying et al., 2016).

5.2. The influence of climate warming on habitat of RRH

The results indicated that a moderate climate warming (RCP4.5) would result in maximum habitat suitability, and then decreased as climate warmed. The Figs. 6 and 7 showed that as the climate warming, the RRH's potential global distribution migrated to high latitude. There was part of the region not suitable for the growth of RRH before, but with increasing of the temperature in the north, the part of unsuitable region changing into low suitable area, and even some low suitable areas have become moderate and highly suitable for RRH. It proved that the high suitability of RRH was increasing in different climate warming scenarios comparing to the present predict result (Table 4). The results showed that the habitat area of high suitable for RRH increased in all of the four climate change scenarios, which may be related to temperature and rainfall, the temperature increment and water cycle increasing may help the growth of RRH. The increase of habitat area was various in different scenarios. The high suitable habitat area reached the largest at RCP4.5 scenario, while the unsuitable habitat area reached the largest at RCP8.5. This suggests that

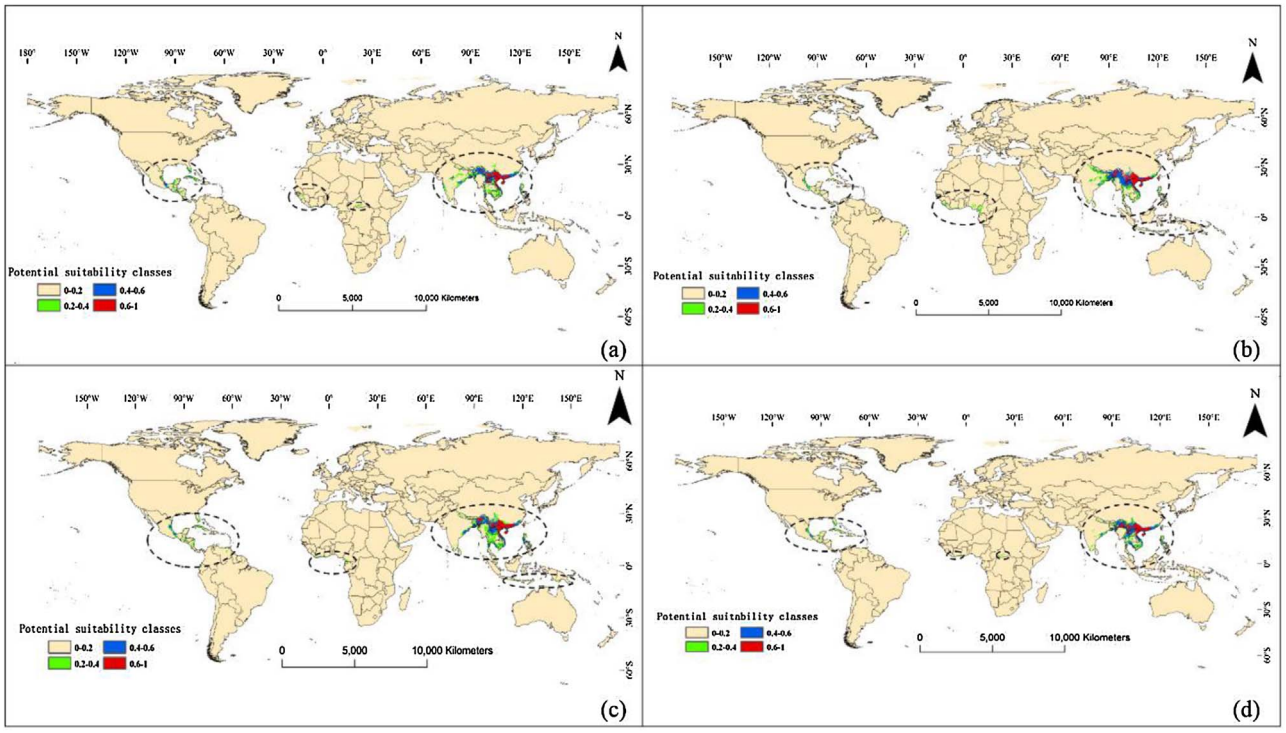

Fig. 6. The potential distribution of RRH under four climate warming scenarios (a, b, c and d represent the four scenarios RCP 2.6, RCP4.5, RCP6.0, RCP8.5 respectively in the world, the main distribution areas are marked by the dotted line.).

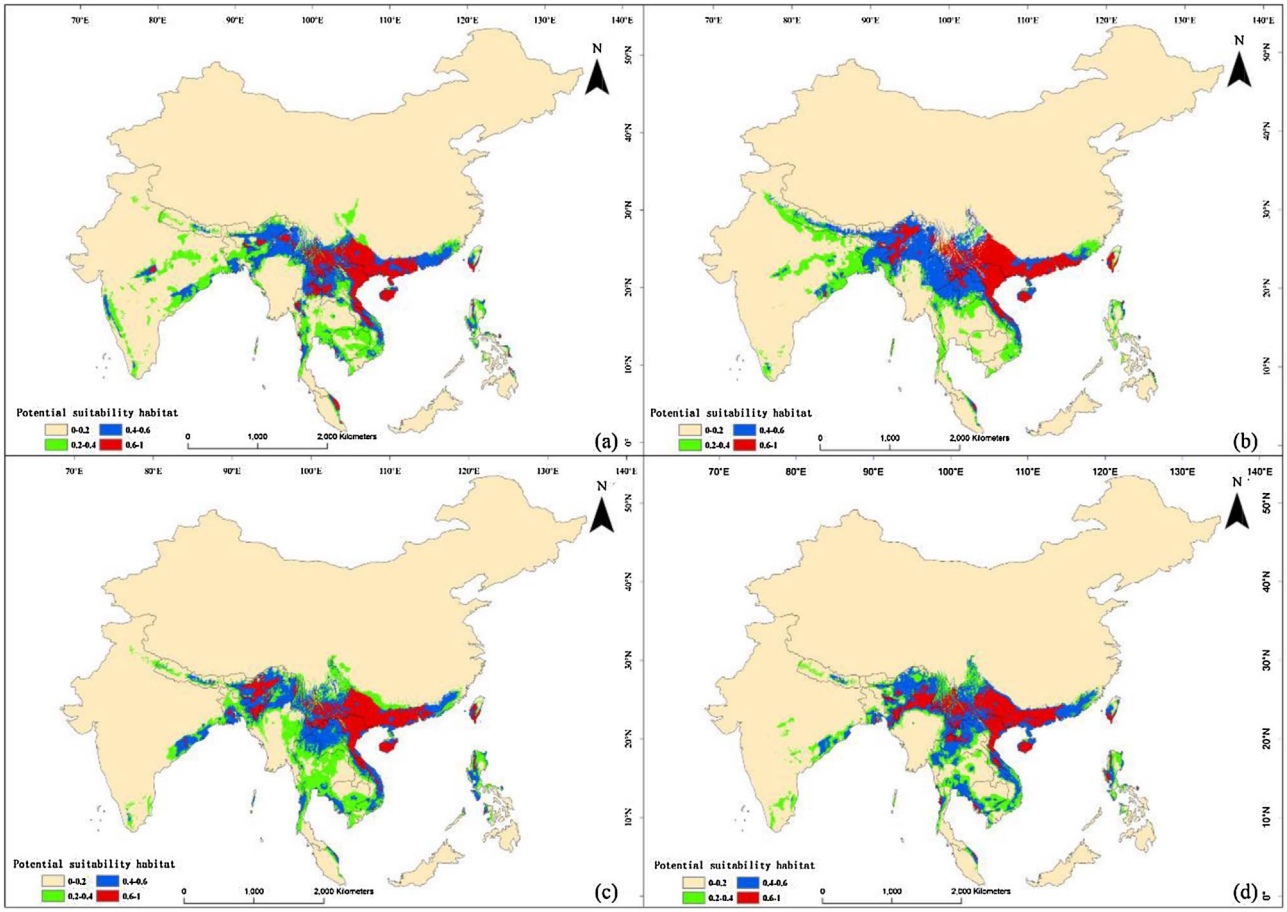

Fig. 7. The potential distribution of RRH under four climate warming scenarios (a, b, c and d represent RCP 2.6, RCP4.5, RCP6.0, RCP8.5 respectively in mainly distribution countries.).

Table 4
The percentage of RRH different suitability under present and four climate scenarios in mainly distribution countries.

Habitat suitability	Present	RCP2.6	RCP4.5	RCP6.0	RCP8.5
0–0.2	82.94%	84.25%	84.13%	83.48%	85.29%
0.2–0.4	8.42%	6.69%	5.44%	6.75%	4.80%
0.4–0.6	5.99%	5.51%	6.15%	5.84%	6.14%
0.6–1	2.64%	3.54%	4.28%	3.93%	3.76%

climate warming may contribute to the growth and recovery of RRH to some extent. However, if the main environmental factors that affect the growth of the plant changed greatly, its habitat area could decline largely. Some researchers have found that different species have different responses to climate change. Iverson et al. (2008) modeled and mapped 134 tree species, found that the habitat area of 66 species increasing at least 10% compare with before area, the rest of 68 have reduced in different degree. Prasad et al. (2016) found that shortleaf pine increased habitat northward by 2100 as the climate warmed. They indicated that the suitable habitat increased maximum area under the harsh scenario of climate change (RCP8.5). While, we found that the appropriate habitat area of RRH in RCP4.5 increasing largest, it illustrated that different plant species had different response mechanisms under climate warming. The results of this paper showed that vegetation would migrate northward with climate warming, which was consistent with Hällfors et al. (2016) who found that the suitable climate for the species tended to shift toward the north and east as the climate change.

Studies have shown that climate warming not only changed the habitat area of vegetation, but also altered the original vegetation community structure (Wu et al., 2016). The dominating species perhaps move to another place or replaced by subdominant species, or superseded via migration of species from other places. Yet, if the climate changes swiftly, and especially if climate change is accompanied by prevalent disturbance, some species and their functions may be lost before those functions can be replaced by either dominance shifts or new migrants. Adaptability of ecosystems to rapid change appears to be related to the diversity of species traits that are available to assume old and new functions (Loreau et al., 2002). This is often referred to as the "insurance" theory of diversity and stability of ecosystems, in which a subdominant species may be poised to replace a dominant one under changing conditions (Loreau et al., 2002). And this may reach a new ecological dynamic equilibrium.

Although the results of model simulation are conducive to the development of potential habitat of RRH with climate warming, according to our actual situation, the RRH habitat is gradually reduced, which may have a great relationship with human activities. In recent years the effects of Rapid human-driven disturbance on the vegetation habitat has become increasingly influential (Hansen and Clevenger, 2005; Hu et al., 2014). Based on life characteristics (hydrotaxis plant) of RRH, here, we discuss the dam construction influence on the habitat of RRH. Dam construction will reduce species richness and diversity of pioneer formations (Cunha and Ferreira, 2012; Yi et al., 2014). Hofkes and Visscher (1986) found that dam construction caused ponds to form, which would lead to habitat fragmentation and even loss. Dam construction and impoundment will destroy upstream habitats, mainly due to the water levels rising dramatically and impoundment of reservoirs has submerged many habitats. So the number of dams, backwater area, and water level fluctuation range were the key factors influencing the habitat fragmentation. Here we selected the Manwan reservoir as representative to investigate and analyze (seen Table 5). The vegetation investigations conducted in Yunnan in 1984 (before the Manwan reservoir's construction in Yunnan Province) and 1997 (after the Manwan reservoir construction) showed that there were at least 4 habitats of the RRH in the Manwan reservoir area in 1984 and that the species abundance was significantly more than 400. However, in 1997, there were no RRHs upstream of the Manwan reservoir to the midstream. There were also no RRHs in the floodplain from the midstream to the downstream. Three habitats disappeared, and only scattered RRHs were distributed in the floodplain between the upstream and the estuary of Luozha River. Even those growths in 1997 were worse than they had been in 1984 (Wang et al., 2000). Notably, the construction of the dam directly leads to the loss of RRH habitat, and made the existing habitat fragmentation intensified.

Table 5
Comparisons of *Homonoia riparia* between before and after Manwan Hydropower dam construction (Zhao et al., 2010).

Habitat number	1		2		3		4	
Time [a]	Before	After	Before	After	Before	After	Before	After
Altitude (m)	922		920		930		985	
Aspect (°)	0		SE40		NW81		NE15	
Slope (°)	0		5		4		5	
Habitat area (m^2)	> 1500	1200	> 200	0	> 200	0	> 200	0
Present/ absent [b]	+	+	+	−	+	−	+	−
Species tall (m)	1.6	1.0	1.7	0	1.2	0	2	0
Species cover (%)	25	2	30	0	30	0	60	0
Species richness	> 200	14	> 50	0	> 50	0	> 100	0

[a] Before dam construction, 1984; After dam construction, 2010.
[b] +, Present; −, Absent.

To sum up, human disturbance can accelerate the migration rate of tree species to the suitable place. For example, clear cutting the northern larch forests in Heilongjiang Province has been associated with shifting northward of the northern boundary of broad-leaved forests by about 290 km between 1896 and 1986 (Chen, 2000). In the next work, we will continue to focus on the impact and disturbance of human activities on vegetation habitat, especially the ecological effects of dam construction.

6. Conclusion

Using maximum entropy theory, based on the presence–only data and environmental data, a habitat suitability model was developed to evaluate and predict the existence and potential habitat of the RRH. Our study showed that model simulation results of potential distribution area are consistent well with the field survey record. The simulation of the AUC value also indicated that the rationality of this simulation. Four factors (including precipitation in July, minimum temperature in July, temperature annual range, and the distance from a river) mainly limit the distribution of RRH. The cumulative contribution of the four factors was as high as 66.9%.

The simulation results indicate that the RRH's habitat suitability at four climate warming scenarios were better than the present situation. From RCP2.6 to RCP4.5, the suitability and the suitable area of habitat will increase as the climate warming. Both the suitability and the suitable area reached optimal conditions at RCP4.5 and then decreased as climate warming from RCP4.5 to RCP8.5. Climate warming is conducive to the RRH's habitat extension and the potential distribution area migrating north as the climate warming. The influence of dam construction on the RRH's habitat showed that impoundment of reservoirs has inundated many habitats, which led to habitat fragmentation and even loss. Studies suggested that choosing the suitable areas for building dam, avoiding vegetation area as far as possible, repairing the destruction of vegetation and expanding destructive vegetation habitat area according to the results of the prediction are considered urgently.

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